Physics and Hybrid Model Approaches for Prognostics and Decision Making

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Agenda

- Introduction to Prognostics
- Introduction to Model-based Prognostics
- Research Approach
- Architecture
- Case Study : Prognostics of Li-Ion Batteries
- Hybrid Modeling for Prognostics
- Closing Remarks

INTRODUCTION TO PROGNOSTICS

Why Diagnostics

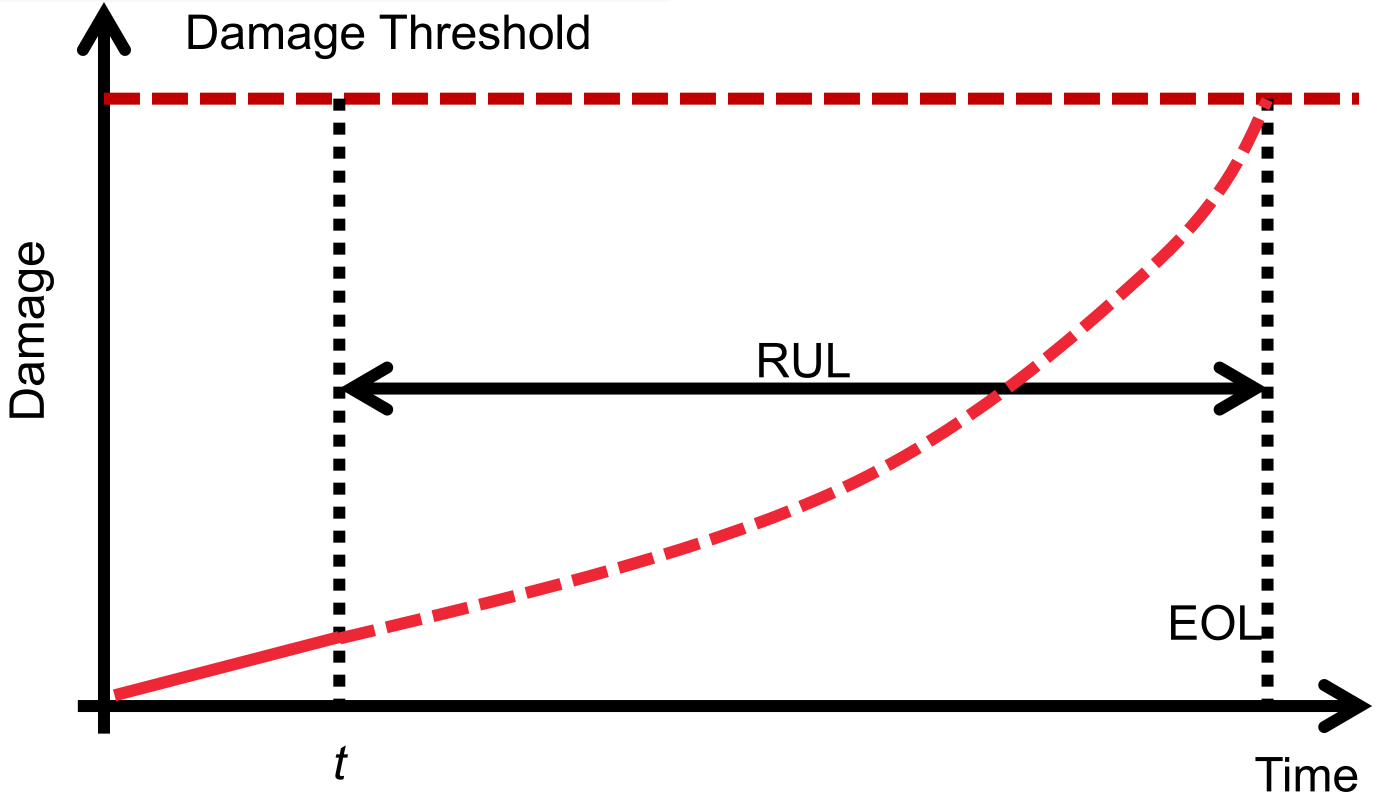
- di·ag·nos·tic
  - a distinctive symptom or characteristic.
    - a program or routine that helps a user to identify errors.
  - the practice or techniques of diagnosis.
    - "advanced medical diagnostics"
  - PHM Community – "Detect and Isolate"
    - Fault Magnitude
    - System/Component

Why Prognostics

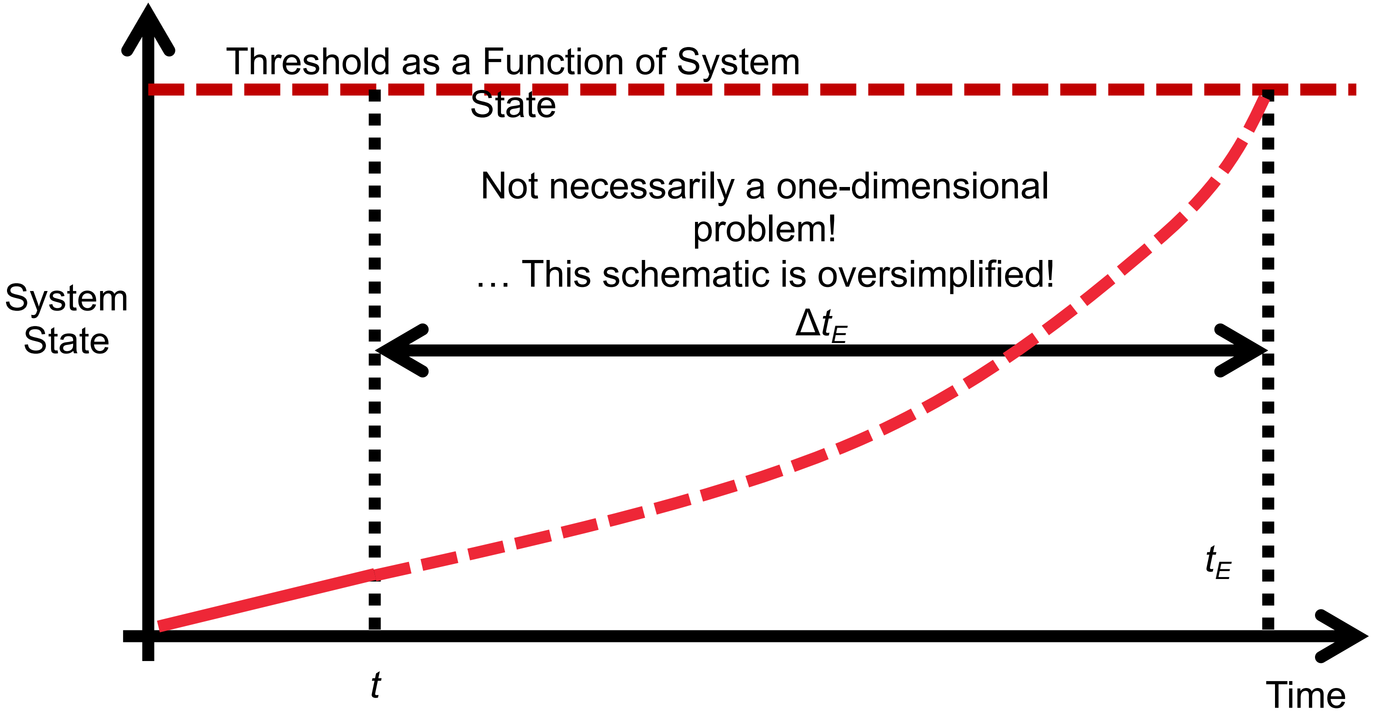
- Safety and Decision Making
- Reliability & Performance
  - product reputation reduced safety factors

- Operational Optimization
  - Prolonging component life by modifying how the component is used (e.g., load shedding/distribution)
  - Optimally plan or replan a mission

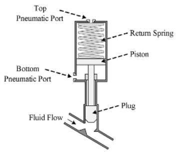
Basic Idea



Basic Idea


Threshold as a Function of System State
Not necessarily a one-dimensional problem!
… This schematic is oversimplified!
System State
Δt_E
t_E
t
Time

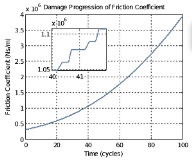
- RUL: Remaining Useful Life
  - Model underlying physics of a component/subsystem
  - Model physics of damage propagation mechanisms
  - Determine criteria for End-of-Life threshold
  - Develop algorithms to propagate damage into future
  - Deal with uncertainty



$$f_g(p_1,p_2)=\begin{cases} C_sA_sp_1\sqrt{\frac{\gamma}{ZR_gT}\left(\frac{2}{\gamma+1}\right)^{(\gamma+1)/(\gamma-1)}}, & p_1\ge p_2\wedge p_1/p_2\ge\left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)}\\ C_sA_sp_1\sqrt{\frac{2}{ZR_gT}\left(\frac{\gamma}{\gamma-1}\right)\left(\left(\frac{p_2}{p_1}\right)^{2/\gamma}-\left(\frac{p_2}{p_1}\right)^{(\gamma+1)/\gamma}\right)}, & p_1\ge p_2\wedge p_1/p_2<\left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)}\\ C_sA_sp_2\sqrt{\frac{\gamma}{ZR_gT}\left(\frac{2}{\gamma+1}\right)^{(\gamma+1)/(\gamma-1)}}, & p_1< p_2\wedge p_2/p_1\ge\left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)}\\ C_sA_sp_2\sqrt{\frac{2}{ZR_gT}\left(\frac{\gamma}{\gamma-1}\right)\left(\left(\frac{p_1}{p_2}\right)^{2/\gamma}-\left(\frac{p_1}{p_2}\right)^{(\gamma+1)/\gamma}\right)}, & p_1< p_2\wedge p_2/p_1<\left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \end{cases}$$

$$f_t(t)=f_g(p_t(t),u_t(t))$$
$$f_b(t)=f_g(p_b(t),u_b(t))$$

$$f_v(t)=\frac{x(t)}{L_s}C_vA_v\sqrt{\frac{2}{\rho}\left|p_{fl}-p_{fr}\right|}\,\mathrm{sign}(p_{fl}-p_{fr})$$

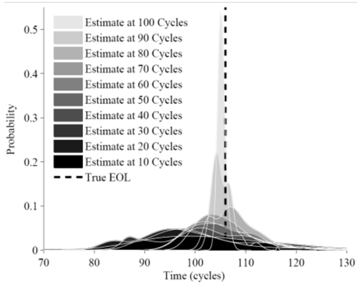


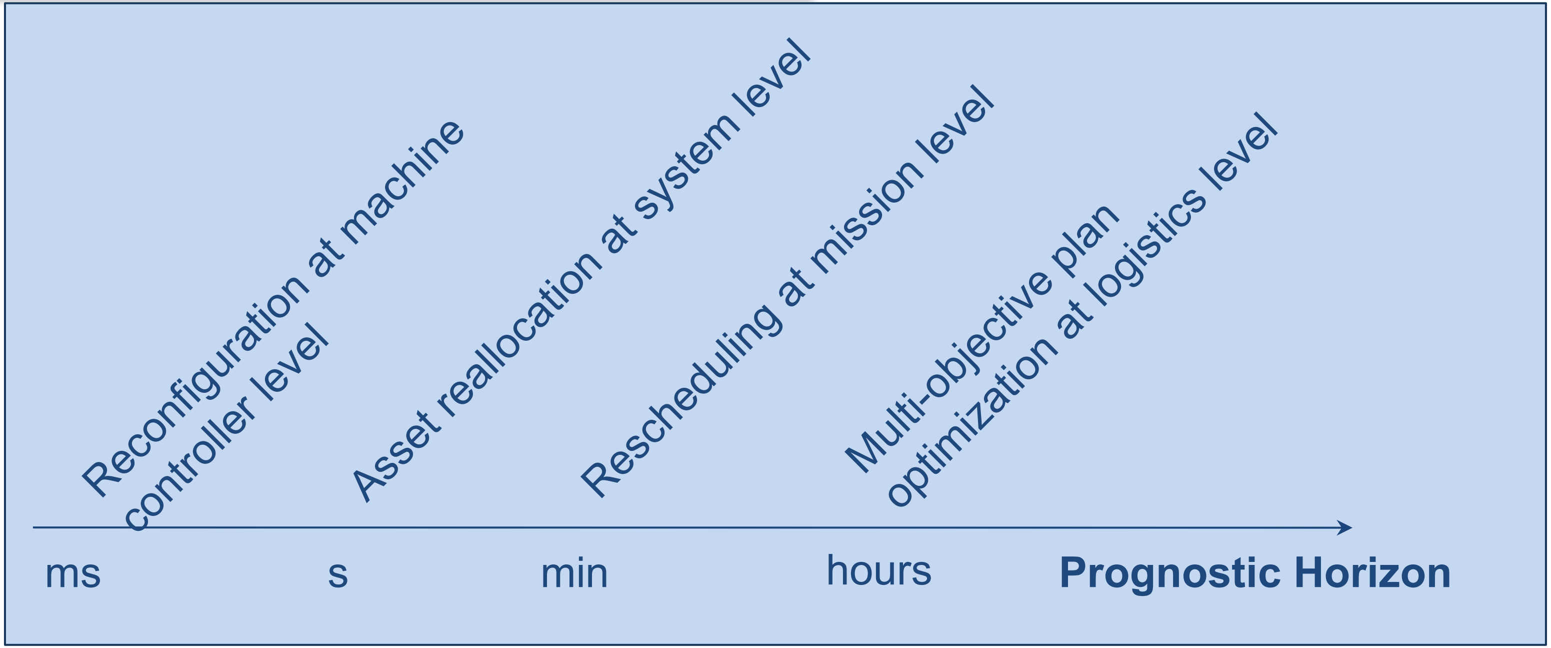
$$\boxed{\dot{r}(t)=w_r|F_f(t)v(t)|}$$

$$EOL(t_P)\triangleq\inf\{t\in\mathbb{R}:t\ge t_P\wedge T_{EOL}(\mathbf{x}(t),\boldsymbol{\theta}(t))=1\}$$

Algorithm 2 EOL Prediction

Inputs: $\{(\mathbf{x}^i_{k_P},\boldsymbol{\theta}^i_k),w^i_{k_P}\}_{i=1}^N$
Outputs: $\{EOL^i_{k_P},w^i_{k_P}\}_{i=1}^N$
for $i=1$ **to** N **do**
  $k\leftarrow k_P$
  $\mathbf{x}^i_k\leftarrow\mathbf{x}^i_{k_P}$
  $\boldsymbol{\theta}^i_k\leftarrow\boldsymbol{\theta}^i_{k_P}$
  while $C_{EOL}(\mathbf{x}^i_k,\boldsymbol{\theta}^i_k)=0$ **do**
    Predict $\hat{\mathbf{u}}_k$
    $\boldsymbol{\theta}^i_{k+1}\sim p(\boldsymbol{\theta}_{k+1}|\boldsymbol{\theta}^i_k)$
    $\mathbf{x}^i_{k+1}\sim p(\mathbf{x}_{k+1}|\mathbf{x}^i_k,\boldsymbol{\theta}^i_k,\hat{\mathbf{u}}_k)$
    $k\leftarrow k+1$
    $\mathbf{x}^i_k\leftarrow\mathbf{x}^i_{k+1}$
    $\boldsymbol{\theta}^i_k\leftarrow\boldsymbol{\theta}^i_{k+1}$
  end while
  $EOL^i_{k_P}\leftarrow k$
end for





Pilots

Air Traffic Control

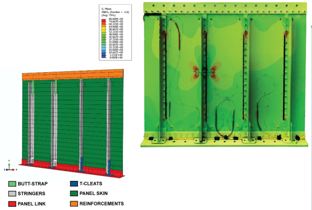
Autonomy.

Airline Operators

Operators

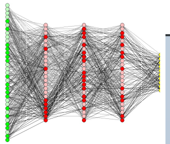
Maintainers

State of the Art



- Results tend to be intuitive
- Models can be reused
- If incorporated early enough in the design process, can drive sensor requirements Computationally efficient to implement
- Model development requires a thorough understanding of the system
- High-fidelity models can be computationally intensive

- Paris-Erdogan Crack Growth Model
- Taylor tool wear model
- Corrosion model
- Abrasion model



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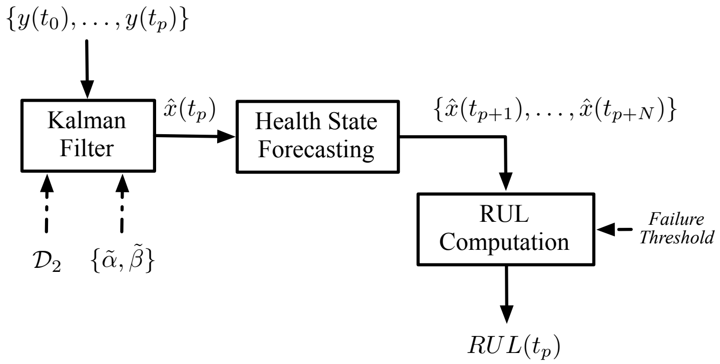
Model-based prognostics

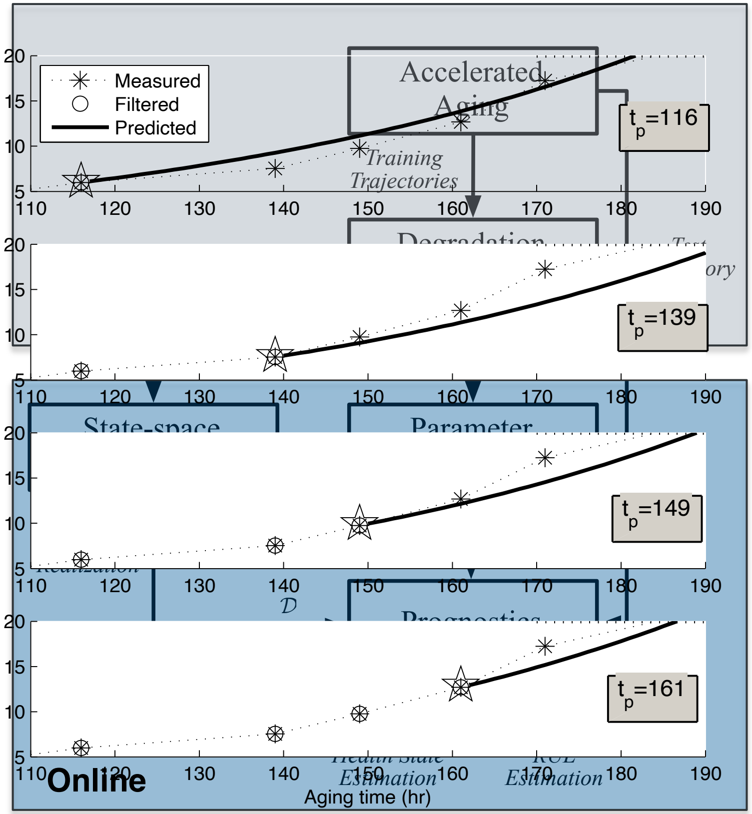
- State vector includes dynamics of normal and degradation process

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$y_k = Hx_k + v_k$$

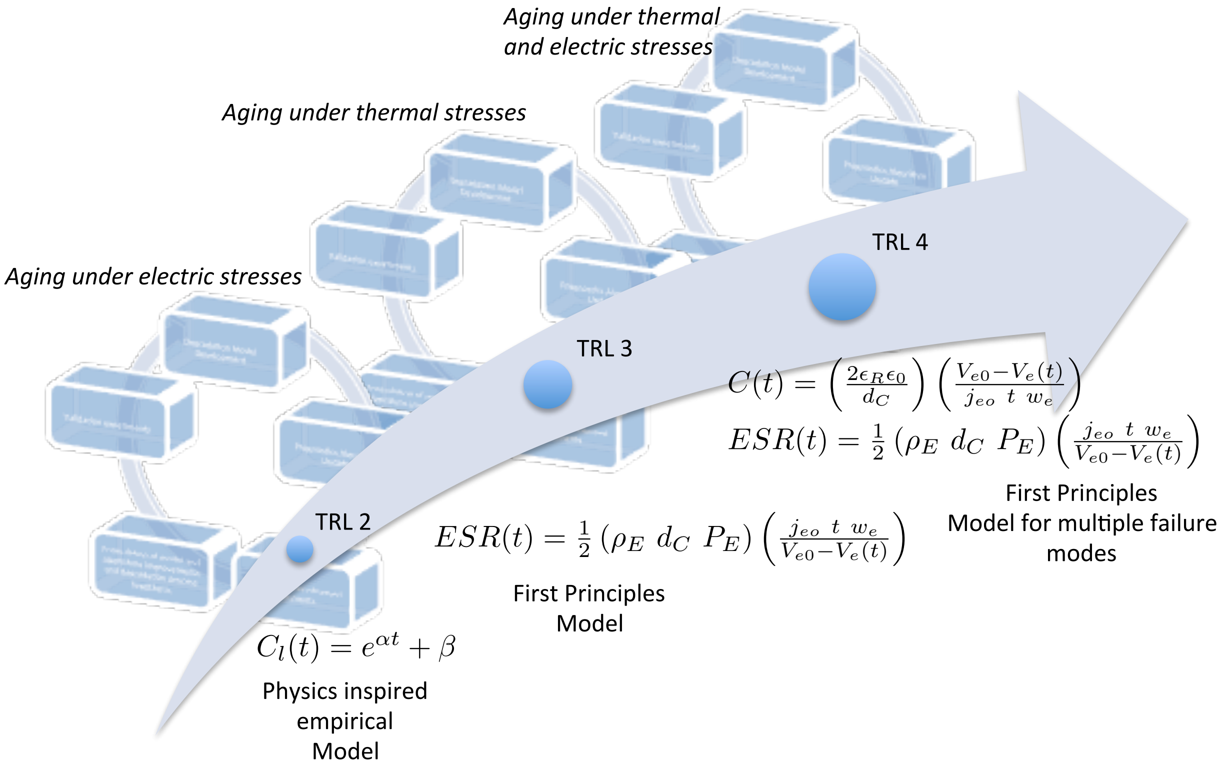


- EOL defined at time in which performance variable cross failure threshold

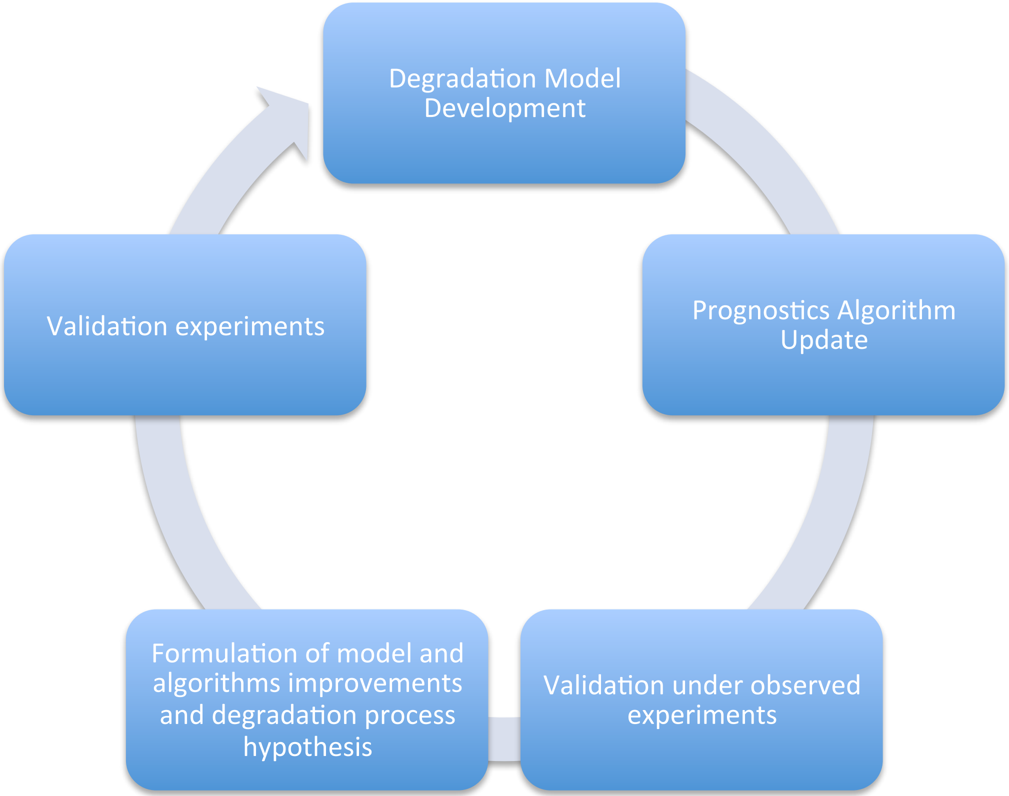
$$R(t_p) = t_{EOL} - t_p$$



Model and Algorithm Maturation



Algorithm Maturation - Validation

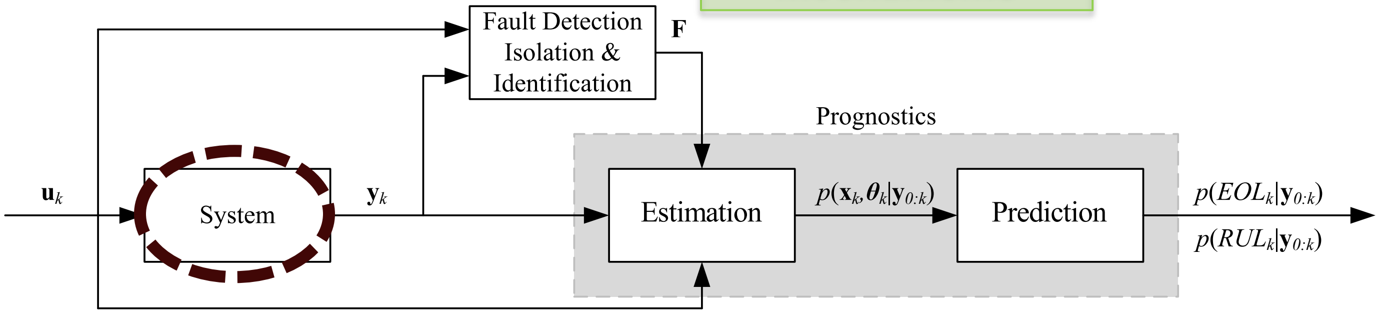


Architecture

Model-Based Architecture

1 System receives inputs, produces outputs

2 Identify active damage mechanisms



3 Estimate current state and parameter values

4 Predict EOL and RUL as probability distributions

Initial Problem Formulation

- Assume we know
  - Initial state, $\mathrm{x}(k_o)$
  - Future input trajectory, $\mathbf{U}_{k_o,k_h} = [\mathrm{u}(k_o), \mathrm{u}(k_o+1), \ldots, \mathrm{u}(k_h)]$
  - Process noise trajectory, $\mathbf{V}_{k_o,k_h} = [\mathrm{v}(k_o), \mathrm{v}(k_o+1), \ldots, \mathrm{v}(k_h)]$
- Problem definition
  - Given $k_o, k_h, \mathrm{x}(k_o), \mathrm{U}_{k_o,k_h}, \mathrm{V}_{k_o,k_h}$
  - Compute EOL
    - $\mathrm{EOL}(k) = \inf\{k' : k' \geq k \text{ and } T_f(\mathbf{x}(k))\}$

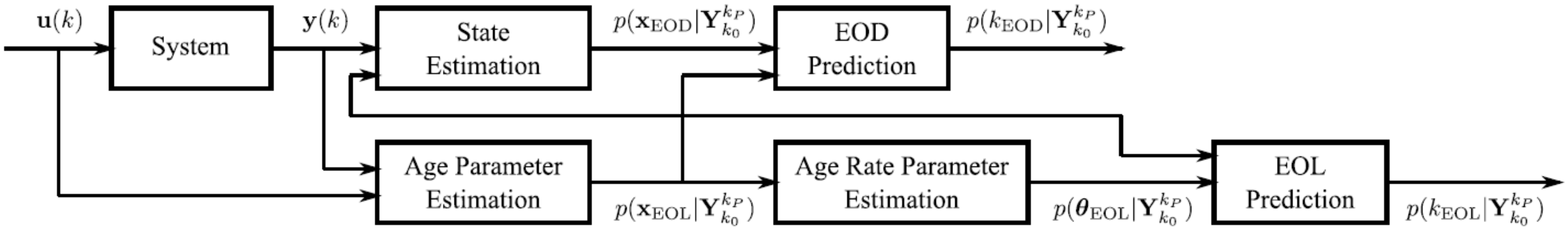
Computational Algorithm

ComputeEOL$\left(k_o, k_h, \mathbf{x}(k_o), \mathbf{U}_{k_o,k_h}, \mathbf{V}_{k_o,k_h}\right)$

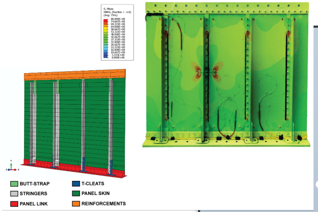
1. $\mathbf{X}_{k_o,k_h}(k_o) \leftarrow \mathbf{x}(k_o)$ // Set initial state
2. **for** $k = k_o$ **to** $k_h - 1$ **do**
3.   **if** $T_f\left(\mathbf{X}_{k_o,k_h}\right)(k)$ // Check if failure state
4.   **return** k // Return current time as EOL
5.   **end if**
6. $\mathrm{X}_{k_o,k_h}(k+1) \leftarrow \mathrm{f}\left(\mathrm{X}_{k_o,k_h}(k), \mathrm{U}_{k_o,k_h}(k), \mathrm{V}_{k_o,k_h}(k)\right)$ // Update state
7. **end for**
8. **if** $T_f\left(\mathbf{X}_{k_o,k_h}\right)(k)$ // Check if failure state
9.   **return** k // Return current time (k_h) as EOL
10. **else**
11.   **return** ∞ // Return infinity
12. **end if**

Integrated Prognostics Architecture

- System (battery) gets inputs (current) and produces outputs (voltage)
- State estimation computes estimate of state given estimates of age parameters
- EOD prediction computes prediction of time of EOD, given state and age parameter estimates
- Age parameter estimation computes estimates of age parameters
- Age rate parameter estimation computes parameters defining aging rate progression
- EOL prediction computes prediction of time of EOL, given age parameter and age rate parameter estimates



State of the Art



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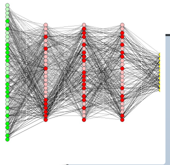

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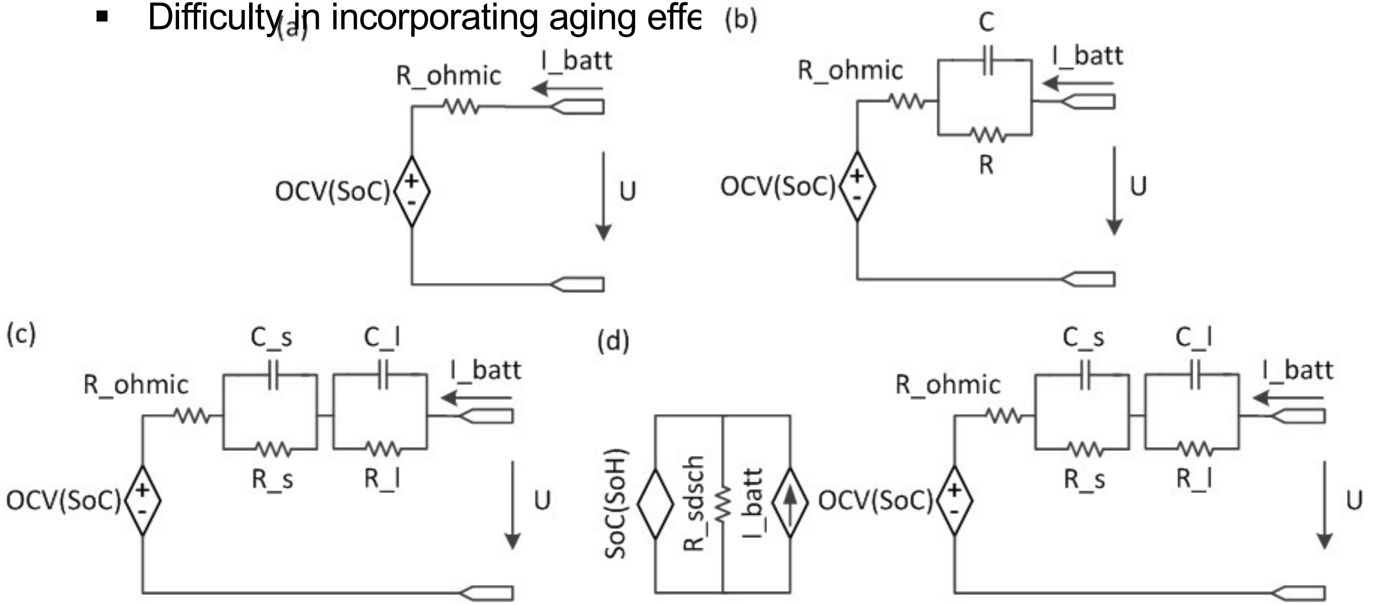
Case Study : Prognostics of Li-Ion Batteries

Battery Modeling

- Equivalent Circuit Empirical Models
  - Most common approach
  - Various model complexities used
  - Difficulty in incorporating aging effe



Battery Model – Tuned using Lab Data

- An equivalent circuit battery model is used to represent the battery terminal voltage as a function of current and the charge stored in 3 capacitive elements

$$x = [q_b \; q_{cp} \; q_{Cs}]^T$$

$$\dot{x} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -\frac{1}{R_{cp}C_{cp}} & 0 \\ 0 & 0 & -\frac{1}{R_s C_s} \end{bmatrix} x + \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix} i + \xi$$

$$y = V = \begin{bmatrix} \frac{1}{C_b} & -\frac{1}{C_{cp}} & -\frac{1}{C_s} \end{bmatrix} \cdot x$$

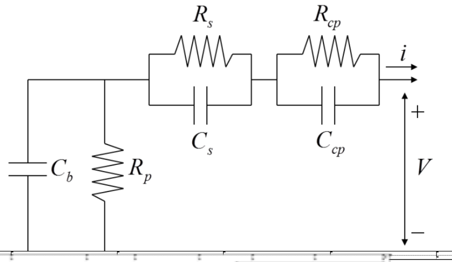
- Two laboratory loading experiments are used to fit the following parameterization coefficier

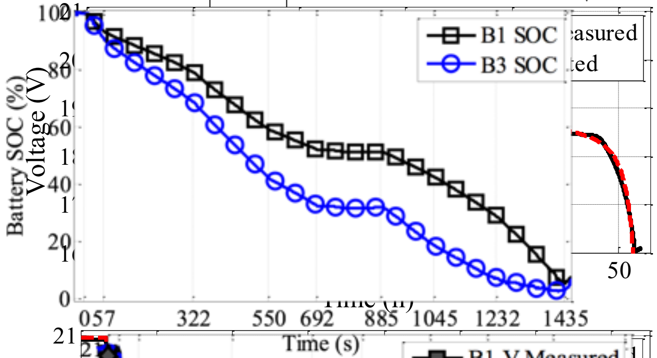
$$\mathrm{SOC} = 1 - \frac{q_{max} - q_b}{C_{max}}$$

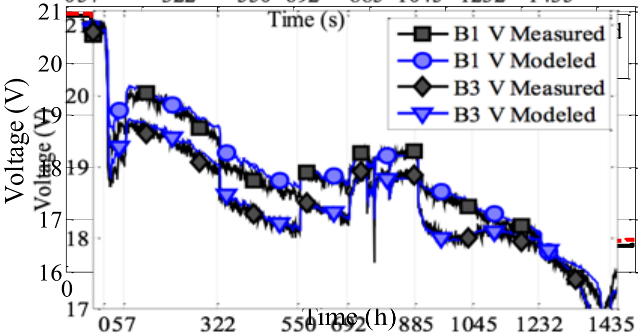
$$C_b = C_{Cb0} + C_{Cb1} \cdot \mathrm{SOC} + C_{Cb2} \cdot \mathrm{SOC}^2 + C_{Cb3} \cdot \mathrm{SOC}^3$$

$$C_{cp} = C_{cp0} + C_{cp1} \cdot \exp\left(C_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

$$R_{cp} = R_{cp0} + R_{cp1} \cdot \exp\left(R_{cp2}\left(1 - \mathrm{SOC}\right)\right)$$

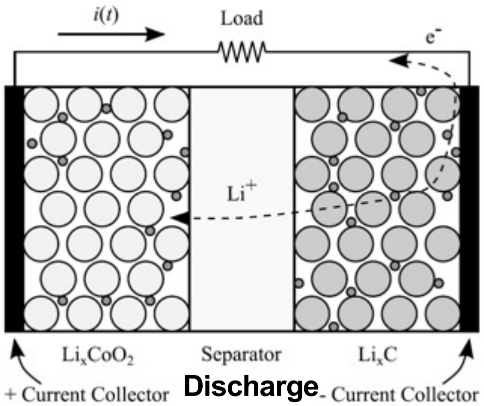






Battery Modeling

- <u>Electrochemical Models vs. Empirical Models</u>
  - Battery physics models enable more direct representation of age-related changes in battery dynamics than empirical models
  - Typically have a higher computational cost and more unknown parameters



Discharge

Reduction at pos. electrode:

$Li_{1-n}CoO_2 + nLi^+ + ne^- \rightarrow LiCoO_2$

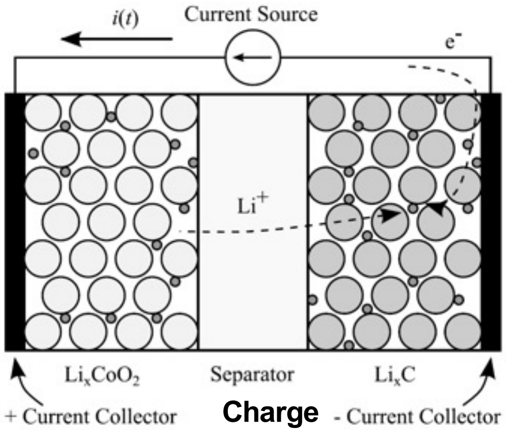
Oxidation at neg. electrode:

$Li_nC \rightarrow nLi^+ + ne^- + C$

Current flows + to –

Electrons flow – to +

Lithium ions flow – to +



Charge

Oxidation at pos. electrode:

$LiCoO_2 \rightarrow Li_{1-n}CoO_2 + nLi^+ + ne^-$

Reduction at neg. electrode:

$nLi^+ + ne^- + C \rightarrow Li_nC$

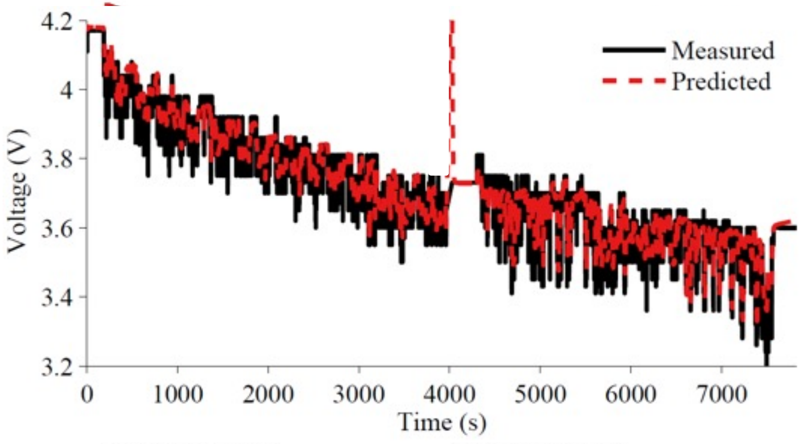
Current flows – to +

Electrons flow + to –

Lithium ions flow + to –

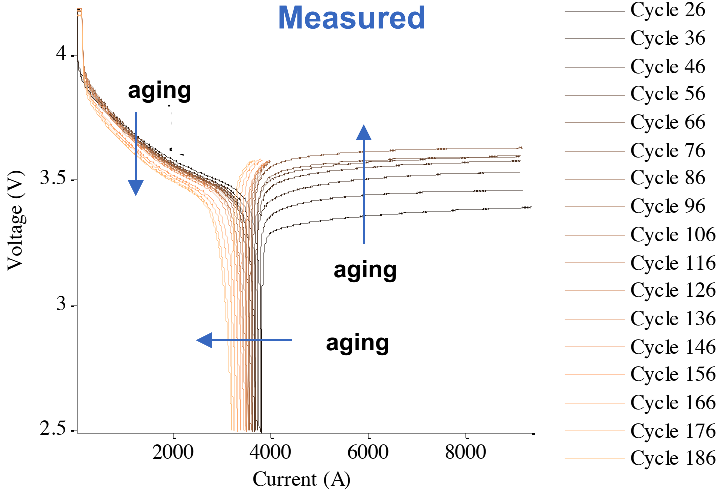
Electrochemical Li-ion Model

- Lumped-parameter, ordinary differential equations
- Capture voltage contributions from different sources
  - Equilibrium potential →Nernst equation with Redlich-Kister expansion
  - Concentration overpotential → split electrodes into surface and bulk control volumes
  - Surface overpotential → Butler-Volmer equation applied at surface layers
  - Ohmic overpotential → Constant lumped resistance accounting for current collector resistances, electrolyte resistance, solid-phase ohmic resistances

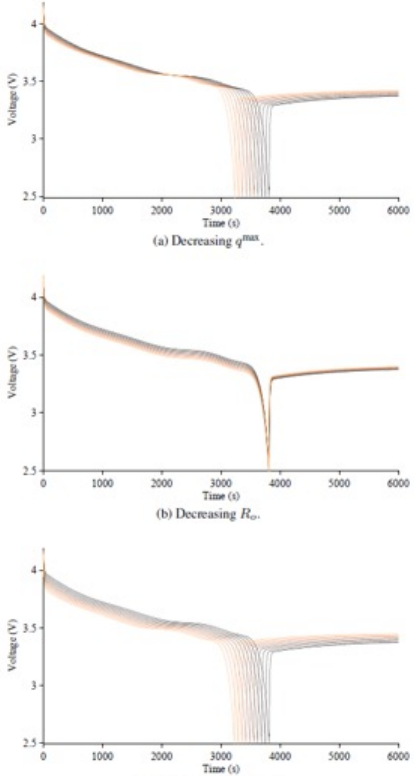


Battery Aging

- Contributions from both decrease in mobile Li ions (lost due to side reactions related to aging) and increase in internal resistance
  - Modeled with decrease in "q^{max}" parameter, used to compute mole fraction
  - Modeled with increase in "R_o" parameter capturing lumped resistances



Simulated



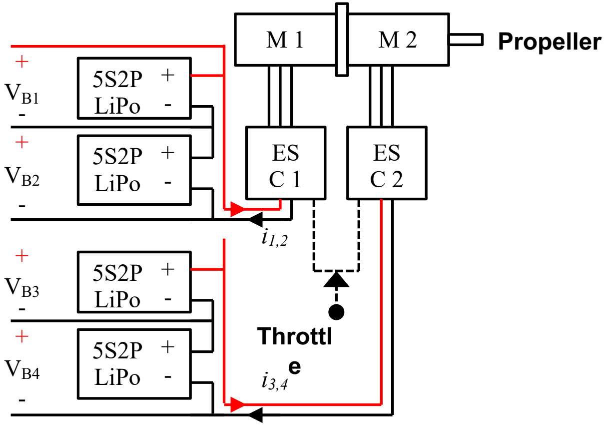
(a) Decreasing q^{max}.

(b) Decreasing R_o.

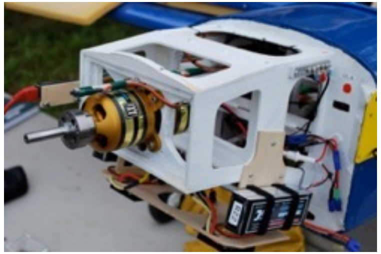
(c) Decreasing q^{max} and R_o.

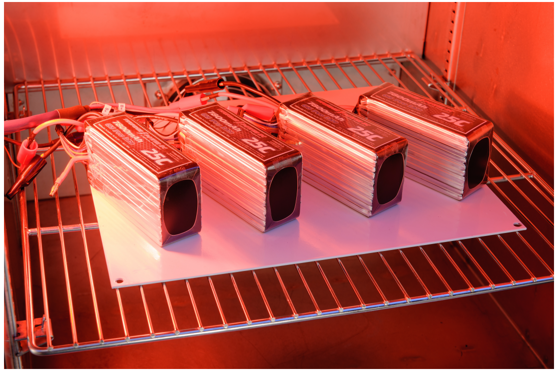
Edge 540-T

- Subscale electric aircraft operated at NASA Langley Research Center
- Powered by four sets of Li-polymer batteries
- Estimate SOC online and provide EOD and remaining flight time predictions for ground-based pilots



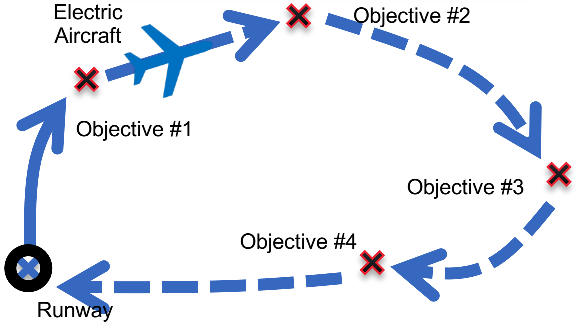
Powertrain





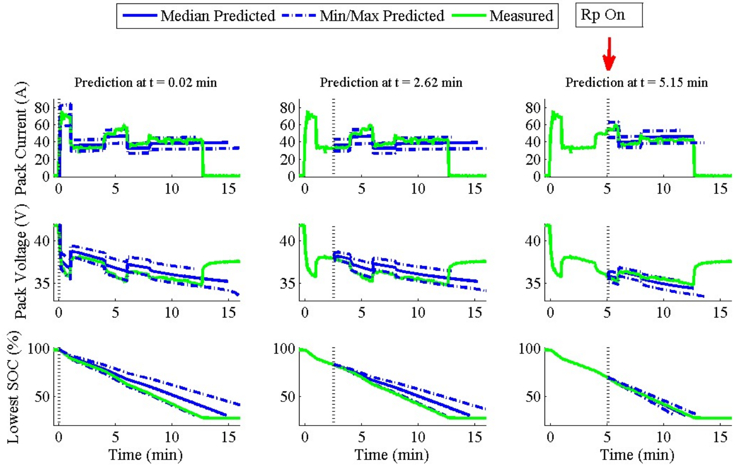
Edge UAV Use Case

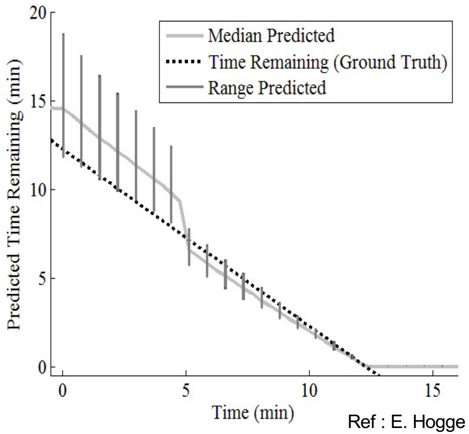
- Piloted and autonomous missions, visiting waypoints
- Require 2-minute warning for EOD so pilot/autopilot has sufficient time to land safely
  - This answer depends on battery age
  - Need to track both current level of charge and current battery age
  - Based on current battery state, current battery age, and expected future usage, can predict EOD and correctly issue 2-minute warning



Predication over Flight Plan

- Measured and predicted battery current, voltage and SOC different time steps
- The min, max and median predictions are plotted from each sample time until the predicated SOC reaches 30%



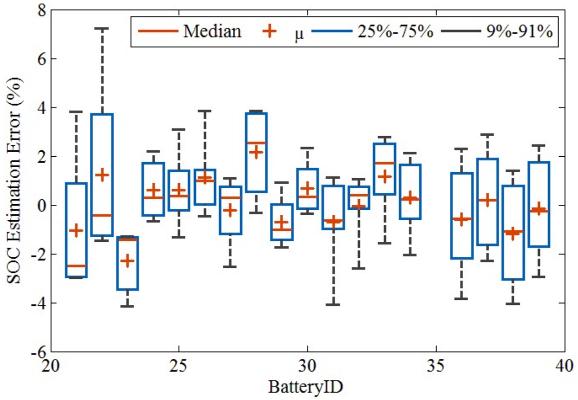


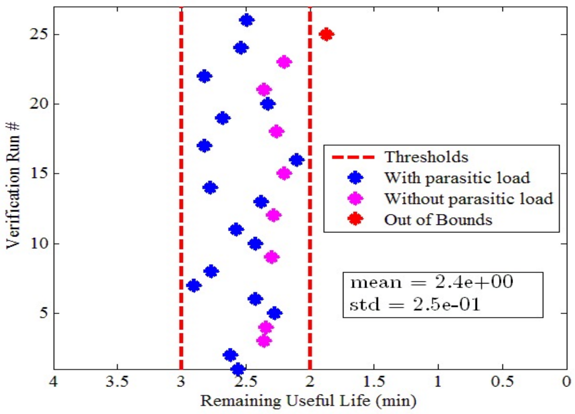
- Predictions for remaining flight time for entire flight plan
- Overestimate till parasitic load is injected
- Once the parasitic load is detected the remaining flying time time prediction shifts down.

Ref : E. Hogge et al, “Verification of a Remaining Flying Time Prediction System for Small Electric Aircraft”, PHM 2015

Performance Requirements

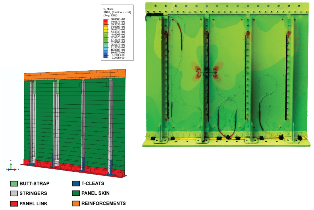
- Accuracy requirements for the two minute warning were specified as:
  - *The prognostic algorithm shall raise an alarm no later than two minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  - *The prognostic algorithm shall raise an alarm no earlier than three minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.*
  - *Verification trial statistics must be computed using at least 20 experimental runs*





Hybrid Approaches

State of the Art



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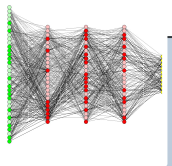

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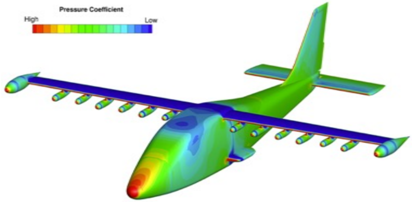
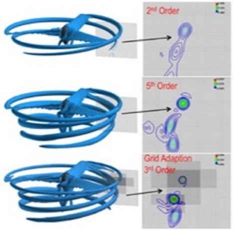
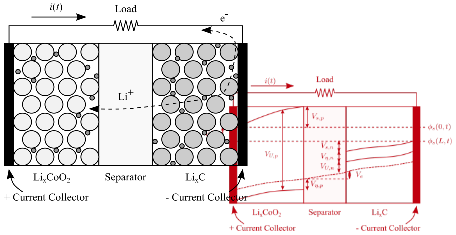
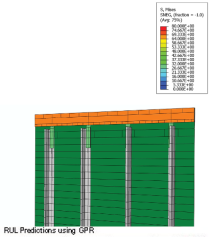
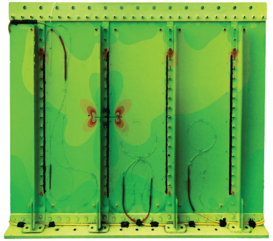
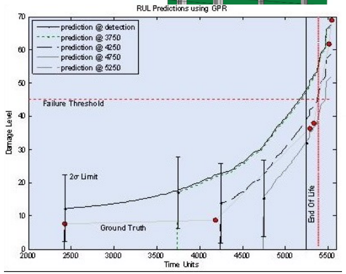

Pressure Coefficient
High
Low

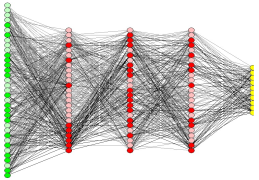

2nd Order
5th Order
Grid Adaption
3rd Order


$i(t)$
Load
e^-
Li^+
Li_xCoO_2
Separator
Li_xC
+ Current Collector
- Current Collector

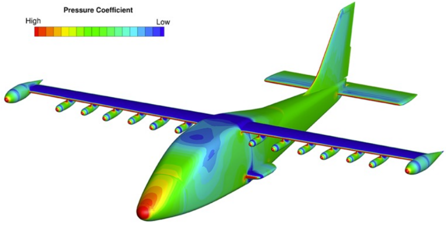


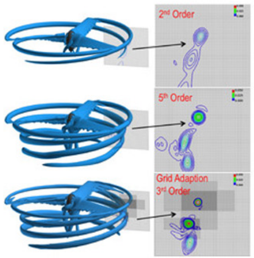


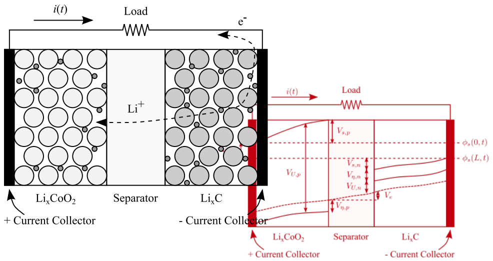

RUL Predictions using GPR
prediction @ detection
prediction @ 3750
prediction @ 4250
prediction @ 4750
prediction @ 5250
Failure Threshold
2σ Limit
Ground Truth
End Of Life
Damage Level
Time Units



Hybrid Approach







Machine-Learning underlying physics parameters

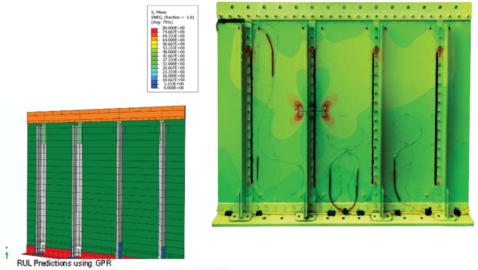
Tensor Flow

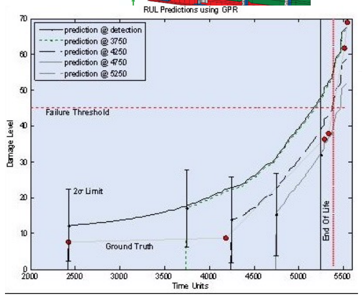
Microsoft Cognitive

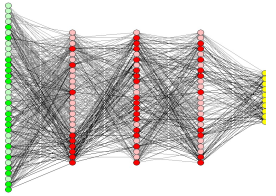
Uber Ludwig

Scikit-learn

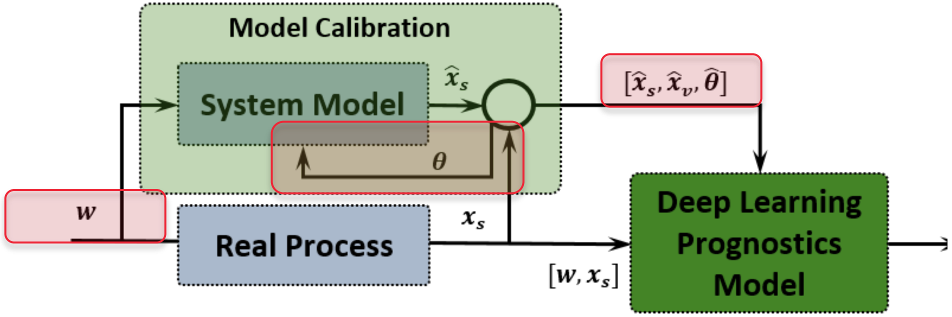
Understanding and Learning underlying Physics for Complex Systems



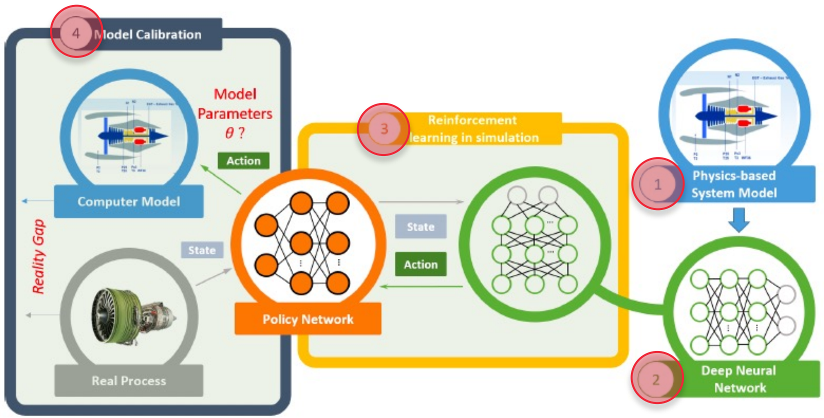




Approach 1 : Deep Learning + Physics Model Calibration



Overall architecture of the hybrid prognostics framework fusing physics-based and deep learning models.

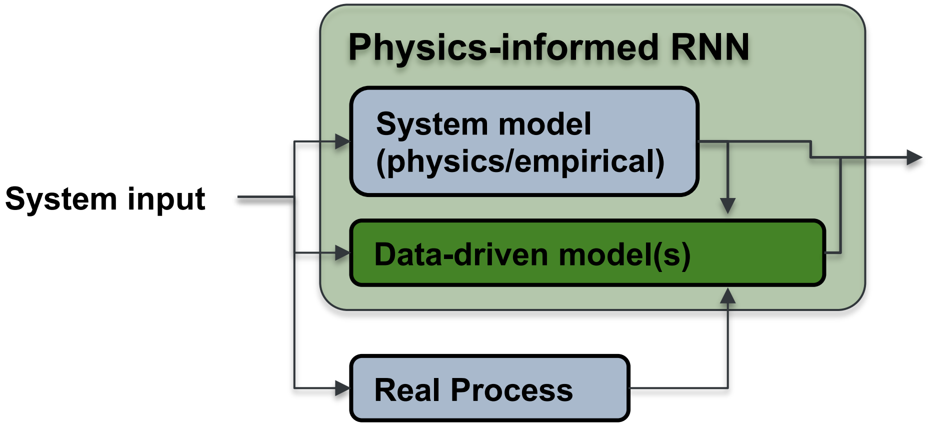


Calibration Policy

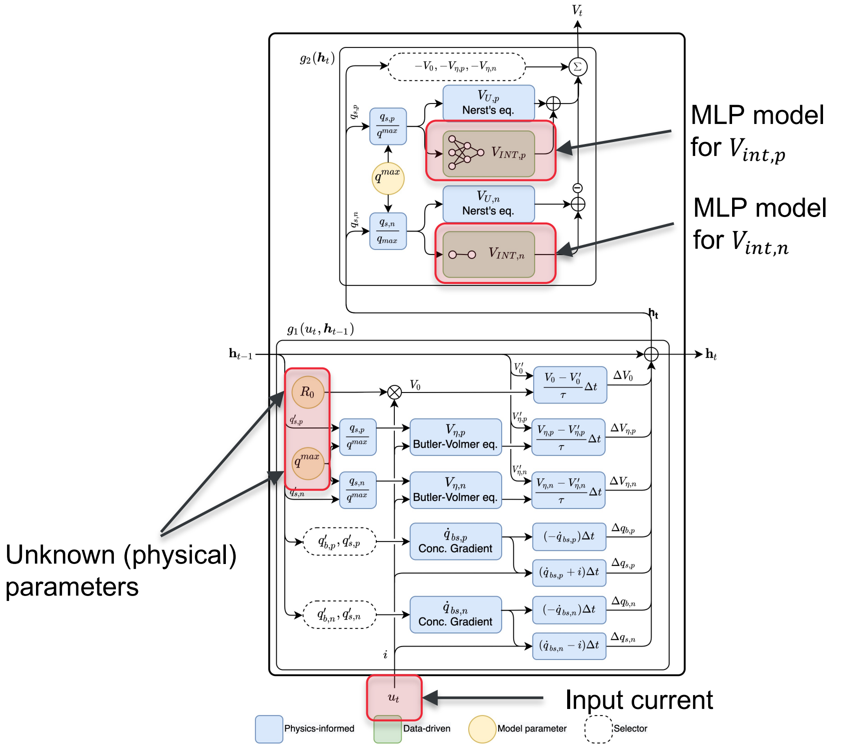
Yuan Tian, Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, Olga Fink, "Real-Time Model Calibration with Deep Reinforcement Learning", arXiv:2006.04001

Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, Olga Fink, "Fusing Physics-based and Deep Learning Models for Prognostics", arXiv:2003.00732

Approach 2 : Physics + RNN



Overall architecture of the physics-informed recurrent neural network

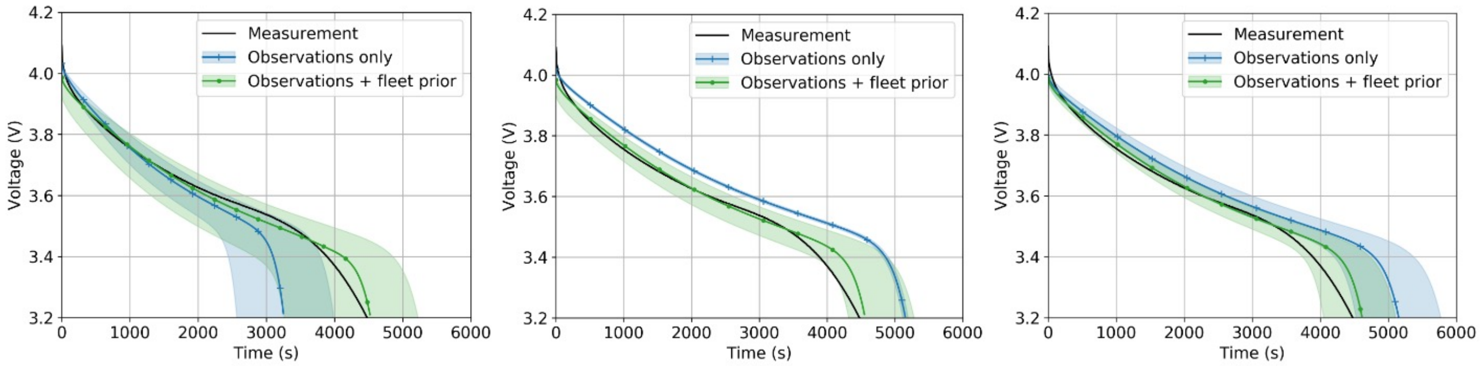


Physics-informed neural network framework for Li-ion Battery SOC estimation

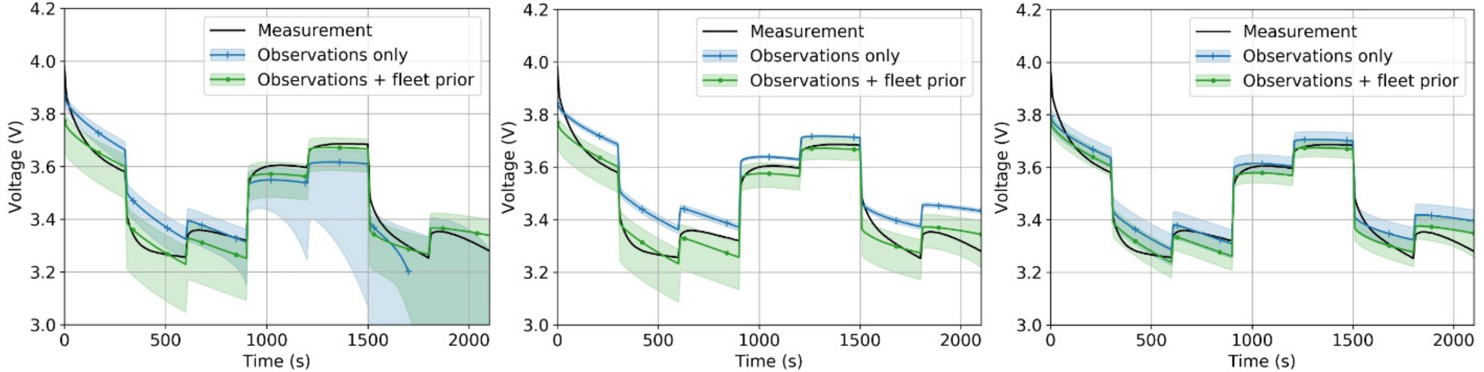
Nascimento, R.G. & Viana, F. A. & Corbetta, M. & Kulkarni, C. S. (2021). "Usage-based Lifing of Lithium-Ion Battery with Hybrid Physics-Informed Neural Networks," AIAA Aviation 2021.

Renato G. Nascimento; Matteo Corbetta; Chetan S. Kulkarni; Felipe A.C. Viana, “Hybrid Physics-Informed Neural Networks for Lithium-Ion Battery Modeling and Prognosis”. Journal of Power Sources 2021 (accepted)

Approach 2 : Physics + RNN

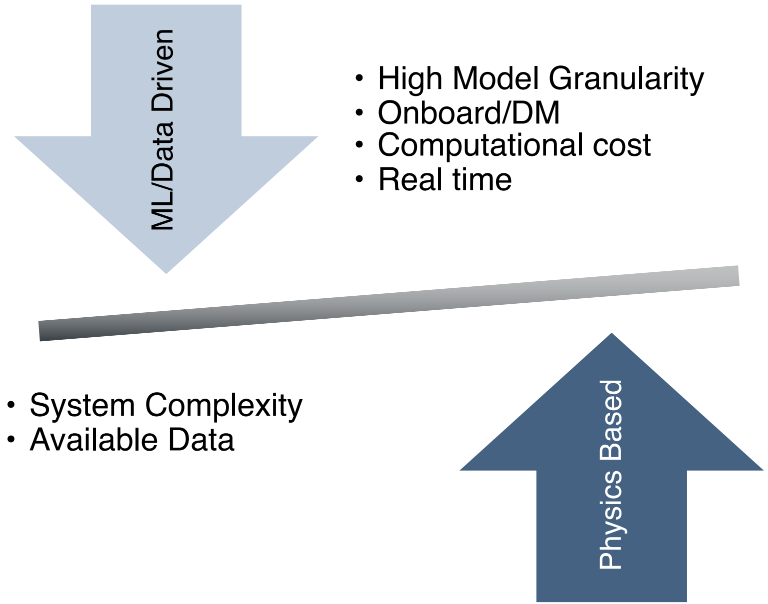


(a) Reference discharge.

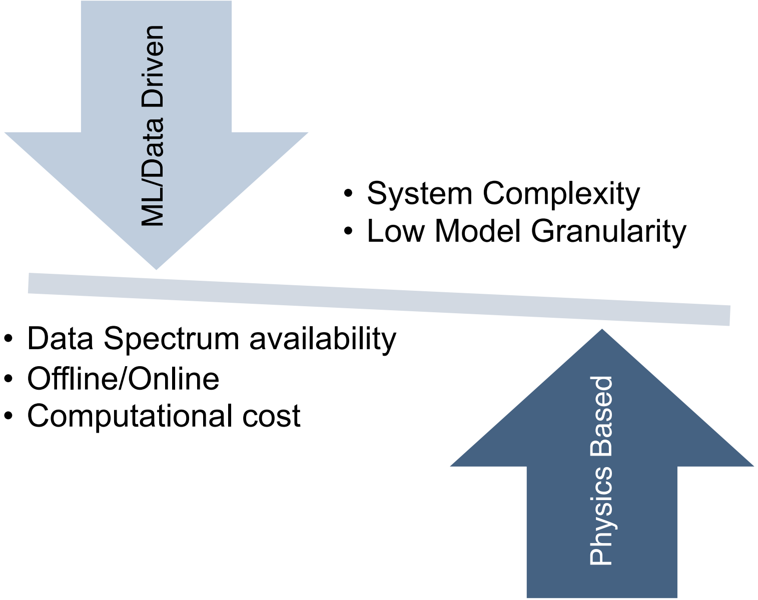


(b) Random-loading discharge.

Next Steps : Looking Ahead



Next Steps : Looking Ahead



- System Complexity
- Low Model Granularity

- Data Spectrum availability
- Offline/Online
- Computational cost

Next Steps : Looking Ahead

Concluding Remarks

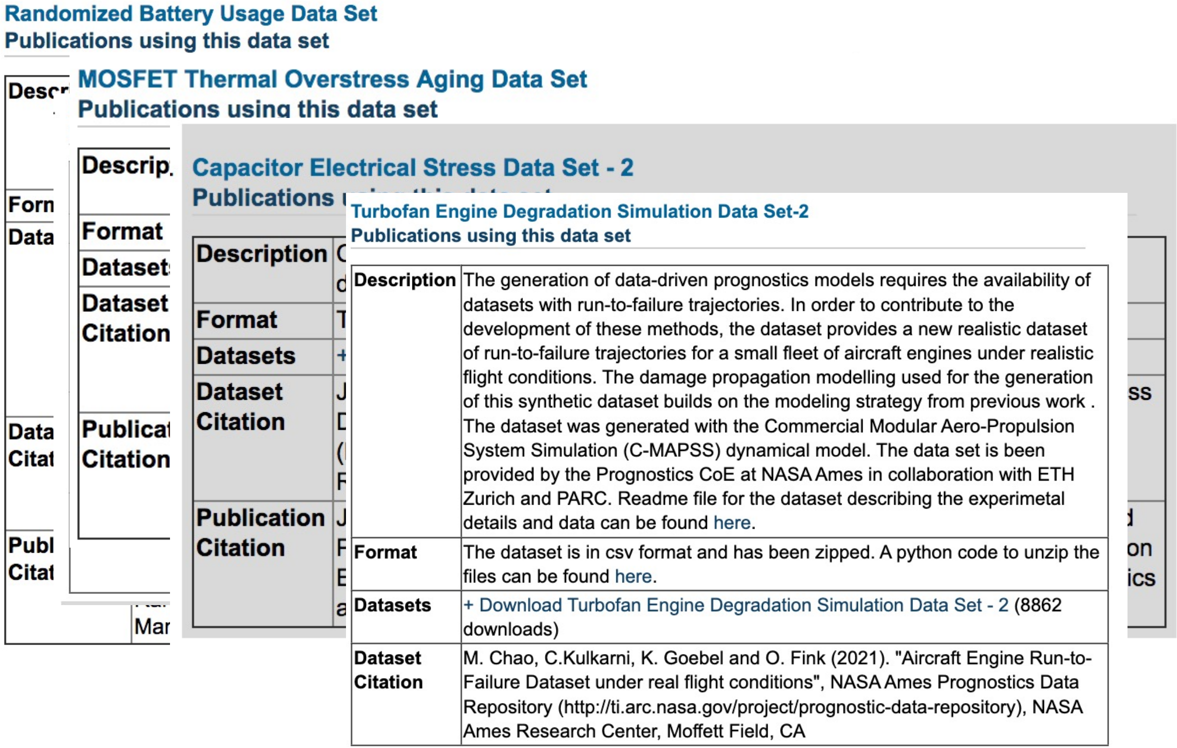
- Health Management framework helps enable
  - Systems safe and efficient
  - Decision making
- Research approach challenges
  - How to balance lack of knowledge of the system vs own expertise on particular PHM tools
- Validate models and algorithms with data from lab experiments and fielded systems

Concluding Remarks

- Hybrid Approaches
  - Physics based methods can be combined with machine learning to determine and evaluate models for complex physical systems.
    - High Fidelity simulation
    - Field and Tests
  - These models enable in verification and validation for autonomy in shorter period of time than current state of the art.
    - Computational tools are two slow.
  - With availability of test and field data, machine learning able to blend the digital data fabric for model update
  - Uncertainty Quantification
- Requirements for autonomous systems

Data Repository – Open Source

https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/



Randomized Battery Usage Data Set

Publications using this data set

MOSFET Thermal Overstress Aging Data Set

Publications using this data set

Capacitor Electrical Stress Data Set - 2

Turbofan Engine Degradation Simulation Data Set-2

Publications using this data set

Description	The generation of data-driven prognostics models requires the availability of datasets with run-to-failure trajectories. In order to contribute to the development of these methods, the dataset provides a new realistic dataset of run-to-failure trajectories for a small fleet of aircraft engines under realistic flight conditions. The damage propagation modelling used for the generation of this synthetic dataset builds on the modeling strategy from previous work . The dataset was generated with the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) dynamical model. The data set is been provided by the Prognostics CoE at NASA Ames in collaboration with ETH Zurich and PARC. Readme file for the dataset describing the experimetal details and data can be found here.
Format	The dataset is in csv format and has been zipped. A python code to unzip the files can be found here.
Datasets	+ Download Turbofan Engine Degradation Simulation Data Set - 2 (8862 downloads)
Dataset Citation	M. Chao, C.Kulkarni, K. Goebel and O. Fink (2021). "Aircraft Engine Run-to-Failure Dataset under real flight conditions", NASA Ames Prognostics Data Repository (http://ti.arc.nasa.gov/project/prognostic-data-repository), NASA Ames Research Center, Moffett Field, CA

Thank You

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https://ti.arc.nasa.gov/tech/dash/groups/pcoe/